Detecting Changes of Transportation-Mode by Using Classification Data

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***Abstract*—Several techniques aim to classify human activity using data from sensors e.g., GPS, accelerometer, Wi-Fi and GSM. The sensor data allow inferring transportation modes as car, bus, walk, and bike. Despite some techniques show improvements in accuracy, researchers constantly deal with issues such as over-segmentation and low precision in trip reporting. Journeys are over-segmented due to the ambiguous situations, for instance: traffic lights, traffic jam, bus stops and weak signal reception. Thereby, current techniques report high misclassification errors. We present a method for detecting changes of transportation mode on a multimodal journey, where the input data regard to the classification of human activities. We use a space transformation for extracting features that identify a transition between two transportation modes. The data are collected from the Google API for Human Activity Classification through a crowdsourcing-based application for smartphones. Results show improvements on precision and accuracy in comparison to initial classification data outcomes. Therefore, our approach reduces the over-segmentation for multimodal journeys.**

keywords: Segmentation, change mode detection, activity classification

I. Introduction

Nowadays, mobiles phones are ubiquitous devices that allow collecting data from the built-in sensors such as accelerometer, gyroscope, compass, Bluetooth, NFC[1], GSM[2] and wireless radio. We refer to data from these sources as *low-level data*. Based on these characteristics of mobiles phones, several approaches for detecting the human activity have been presented. Most approaches base their classifications on GPS and accelerometer data [1] [2] [3] [4], since they provide more information for inferring the transportation mode. However, those approaches suffer from a lack of precision on trip reporting or they are limited to single modal detection.

Multimodal journeys occur very often in the daily life. People use more than one transportation mode for daily journeys. For instance, considering a journey for going to work, it can include a flow of activities as follows (i) walk to the bus station, (ii) go on the bus, and (iii) walk at office. In the previous example we can identify three transportation modes walk, bus and walk respectively. However, the techniques on Human Activity classification may split that journey in more than three modes, thus it causes over-segmentation on journey [5] and inaccuracy on trip reporting. These problems are presented because some features of low-level data are similar in various transportation modes as riding a bike, tram, car and even walk; specially in cases, when the bus is stopped or slows down the speed. Besides, GPS data may be incomplete or inaccurate, causing problems for correct imputation of activities patterns [6].

This work is focused on detecting changes of transportation mode for multimodal journeys. It improves the journey segmentation, particularly on ambiguous situations where misclassifications take place. Moreover, the reduction of over-segmentation benefits the activity classification accuracy, since it identifies segments where a unique transportation mode is performed.

Our approach works on data of human activity classification instead of low-level data. The data are collected from the Google Human Activity Classification (GHAC) API[3]. First, the data are preprocessed for removing inconsistencies either incomplete trips or unlabeled data. Second, the sample data space is transformed into an orthogonal space. Third, we extract six features using a sliding window method along the data, those features are the projected angles. Finally, we use a state vector of projected angles for identifying to the change modes.

II. Materials and Methods

A. Preliminary

We address a preliminary terminology used in activity classification within the context of transportation.

A *transportation mode* specifies the different kind of transportation facilities, that are used to transport people [7]. The transportation can include vehicles such as bus, tram, train,

[1]Near field communication (NFC)

[2]Global System for Mobile communications (GSM)

[3]Google API reference https://developer.android.com/reference/com/google/android/gms/location/DetectedActivity.html

car, motorcycle, and bicycle. Although, walking does not use any transport, it is considered as a transportation mode as well. An *activity* groups one or more transportation mode into categories, for our purpose we consider only three activities such as walking, biking and driving. Since, these activities involve motion from one location to another. The driving activity aggregates the transportation modes such as bus, tram, train, car, and motorcycle. A *change point* refers to a transition from one transportation mode to another, furthermore, a new transportation mode or segment is defined when there is a change from one form of transportation to another [8]. Besides, walking is an important mode to identify changes of transportation, considering that an individual needs walking to transform from one transportation mode to another [5]; and a journey can be partitioned into a walk segment and a non-walk segment by a change point [9]. Thus, there is a change of transportation mode, when the transportation mode at time t is not equal to the next mode at time $t+1$, and one of them is a walking mode.

B. Collecting data

The data collection was performed using the a crowdsourcing-based application developed by Ghent University called *Connect* [10]. It runs on android-based devices and collects measurements such as, GPS locations, accelerometer data, and activity classification data, which are stored on a central database. *Connect* allows to an individual starting a journey with a preselected transportation mode, then make a pause and change for another mode, this step can be repeated anytime; and finally stop the data collection when the journey is over. An individual can select up eight transportation modes on *Connect*, such as on foot, by bike, motorcycle, train, tram/metro, bus, car as driver, and car as passenger; these modes represent labels on the measurements.

Connect also collects the measurements provided by the GHAC API; these measurements represent the probabilities of performing an activity such as driving, biking, walking, still, tilting, and unknown. The API defines those activities as follow: *driving*, probability of device is in a vehicle, such as a car; *biking*, probability of device is on a bike; *walking*, probability of device is on a user who is walking or running; *still*, probability of device is still (not moving); *tilting*, probability of device angle relative to gravity changed significantly; and *unknown*, probability of unable to detect the current activity.

We are interested on activities that include motion; therefore we select inputs such as *driving*, *biking* and *walking* from the activity classification data. Although, the activity *still* could be an indication of change, for instance, an individual can walk to station and wait, either sitting or standing before getting on the bus. However, it may also be possible that the individual decides not to wait anymore and continues walking. In this case, the individual keeps the initial transportation mode, e.g. there is not a change of transportation mode. Thus, we are focused on activities with motions rather than *still* and *tilting*.

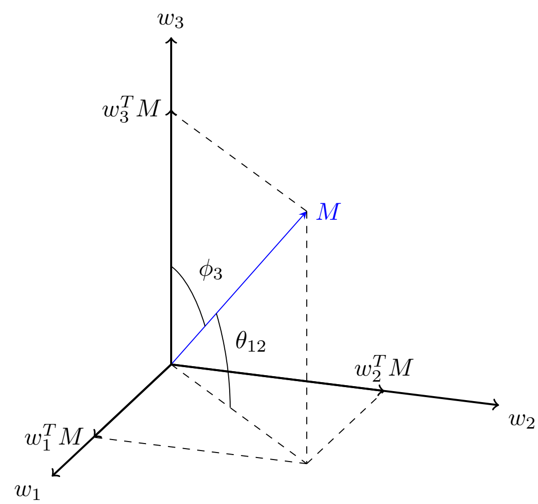

Fig. 1: Activity vector and its projected angles

C. Preprocessing data

Data collection process is not error free; thereby, the data may include either incomplete journeys or unlabeled data. A journey is completed, when it has a start and end entry on the database. A preprocessing stage detects incomplete journeys and unlabeled data. The incomplete journeys are excluded from the data sample, since we aim to identify the changes of transportation, and an incomplete journey does not provide enough information for that purpose. Furthermore, each journey has an identification field, which is provided by *Connect* in order to group the measurements. However, some observations contain missing data on the identification field. Thus, the missing data are filled out using the previous observation, when the interval between observations is lower than third quartile of the sampling period. Namely, the missing observation is part of the same journey. It is important to remark that, this stage does not modify the classification measurements.

D. Sliding windows

A sliding window method is used for processing in sequential order the stream of GHAC data captured by *Connect*. This method allows extracting more information; since the original data contains peaks and values with a high variability, as a consequence, false changes of transportation mode could be detected on the journey. The sliding window smooths the data by averaging the low and peak values. Within the window, the observations are mapped into an individual output value [11]. Where, the output is a local estimator of the probability.

Sliding windows were used in [12] [13] [14] [15] for features extraction since this technique allows capture more information by segmenting the data. The window size has a direct influence over the change detection, the bigger windows produce more delay than smaller [16].

E. Approach

We based our approach on representing the GHAC data as components from a vector. It allows combining all inputs into a multidimensional space, where we calculate the vector characteristics such as, magnitude and projected angles. With all these information we make a relationship between the angles for building a vector state, which allows identifying the changes on the transportation mode.

1) Activity Vector: We represent the input data as a vector M, depicted in Fig. 1. The input data are the set of values for the activities defined in section II-B; where the coordinate system is given by a set of orthogonal vectors w_i, which represent the components for each activity. Therefore, let M be the activity vector and w_i the coefficient vectors for each activity dimension, defined as follow: $M = \{m_1, m_2, m_3\}$, where m_i represents the vector components: m_1 driving, m_2 biking, m_3 walking; and $w_1 = \{1,0,0\}$, $w_2 = \{0,1,0\}$, $w_3 = \{0,0,1\}$, where w_i are orthogonal unitary vectors and w_1, w_2 and w_3 represent the axes driving, biking, and walking, respectively; the coefficient vector w_i allows to keep the vector M in an orthogonal system and it could be used to compensate any component later on. As result, the products $w_1^T M$, $w_2^T M$ and $w_3^T M$ represent the projections of M onto each w_i axis.

The *magnitude* of activity vector M is expressed as follow:

$$\|M\| = \sqrt{(w_1^T M)^2 + (w_2^T M)^2 + (w_3^T M)^2} \tag{1}$$

2) Activity angle ϕ: We define the *activity angle* ϕ, as the angle between the activity vector M and its projection with the orthogonal axis w_i.

$$\phi_i = \cos^{-1}\left(\frac{1}{\|M\|}|w_i^T M|\right) \tag{2}$$

where ϕ_1 is the angle between the vector M and w_1 axis; ϕ_2 is the angle between the vector M and w_2 axis; and ϕ_3 is the angle between the vector M and w_3 axis.

3) Comparative angle θ: We define the *comparative angle* $\theta_{j,k}$, as the angle between the activity vector M and its projection onto the plane formed by the axes w_j and w_k, where the axis of activity angle ϕ_i is not part of that plane.

$$\theta_{j,k} = \cos^{-1}\left(\frac{1}{\|M\|}\sqrt{\sum_{i\in(j,k)}(w_i^T M)^2}\right) \tag{3}$$

where θ_{12} is the angle between the vector M and the plane formed by the axes w_1 and w_2; θ_{13} is the angle between the vector M and the plane formed by the axes w_1 and w_3; and θ_{23} is the angle between the vector M and the plane formed by the axes w_2 and w_3.

4) Detecting changes: To detect changes of transportation mode we use the existing relationship between *activity angle* and *comparative angle*, the relationship shows that, if the angle ϕ_i is lower than the angle $\theta_{j,k}$, then the axis w_i is more likely to be the activity, i.e., the activity vector M is closer to the axis w_i than to the others.

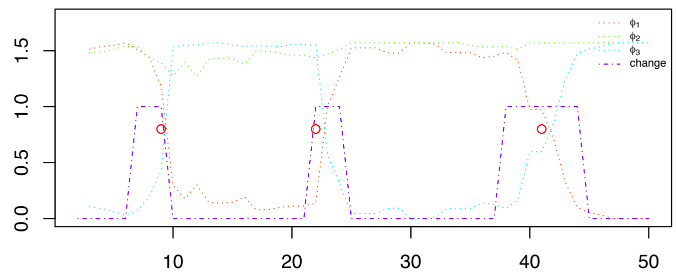

Fig. 2: The detected changes are plotted as red points, the changes are detected where the *activity angle* ϕ decreases its value and the other ones increases it. Besides, the ground truth of changes are labeled as change.

Based on aforesaid relationship, we define S_t that represents a *state vector* of the logical comparison between the angles ϕ and θ at time t.

$$S_t = \left\{\begin{array}{c} \phi_{1t} < \theta_{23t} \\ \phi_{2t} < \theta_{13t} \\ \phi_{3t} < \theta_{12t} \end{array}\right\} \tag{4}$$

Thereby, we detect a *change mode* C_t, when the transition from a state S_t to the next state S_{t+1} shows differences between those states.

$$C_t = \begin{cases} 1 & \text{if } S_t \neq S_{t+1} \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

Furthermore, we consider a *false detection*, when there are two consecutive changes, i.e., the change is detected at time t and then another change is detected at time $t+1$. It may mean the individual went back to the initial transportation mode in a very short period. Hence, these consecutive changes are considered as false detections.

$$\text{false detection} : C_t = C_{t+1} \tag{6}$$

Detecting the false changes of transportation increase the precision, hence it assess a better accuracy. The false changes are the consequence of small variation between the transportation modes; it can also be seen as an uncertainly on the classifier side.

F. Error metrics

To assess the error in our approach, we use the metrics such as precision, recall, and accuracy, which are defined as follows:

$$\text{Precision} = \frac{tp}{tp + fp} \tag{7}$$

$$\text{Recall} = \frac{tp}{tp + fn} \tag{8}$$

$$\text{Accuracy} = \frac{tp + tn}{tp + tn + fp + fn} \tag{9}$$

where tp, fp, tn and fn stand for true positive, false positive, true negative and false negative respectively.

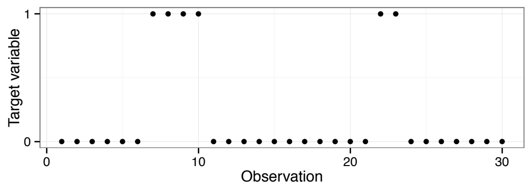

Fig. 3: The target variable is binary and the value of 1 represents a change, although a continuous sequence of 1s is equivalent to a single change.

Precision is the proportion of detected change modes when the approach detects a change of transportation mode that actually occurred. *Recall* is the proportion of real change modes that have been correctly detected. *Accuracy* is the proportion of true results i.e., it is the right detection of change and non-change modes.

III. Experimental results

A. Dataset

We tested our approach in the city of Ghent, Belgium. The data were gathered from daily situations such as go work, go home, and go shop.

Our dataset consists of 71 journeys, which represents 633.6 kilometers and 49 hours. The journeys include transportation-modes such as tram, train, bus, bicycle and walk.

The dataset contains 4116 observations, where each observation represents the probability of performing the activities such as driving, biking, and walking at time t_i. The sampling period is not fixed, it was on average 44 seconds.

The observations are labeled with a *transportation mode* assigned by the user through *Connect*, and it could have values either bus, car, tram, train, foot, bike, motorcycle, and passenger. These labels represent our ground truth and will help us to build the target variable. Besides, the driving activity concerns the transportation mode such as bus, train, tram and car.

1) Target variable: The target variable represents whether or not there is a change of transportation mode, thus it is a binary variable where 1 stands for a change mode and 0 otherwise. We build it using the transportation mode labels i.e., for each transition between distinct values of transportation mode the target variable gets value 1. Those transitions, moreover, may represent more than one observation, especially when an individual is waiting for his next transportation. Thereby, a change of mode can be represented by a sequence of ones as well.

For instance, the data sample in Fig. 3 contains 30 observations, where 24 observations are zero and 6 observations are one, although there are only 2 change of mode.

The target variable has skewed distribution, where the changes are 12% of the data and the non-change is 88%, it can be explained by the data origin, since an individual can switch often as much two transportation in a multimode journey, thus more samples are collected as non-change.

TABLE I: Table of window size δ

	δ=2	δ=3	δ=4	δ=5	δ=6
Precision	67.0%	74.0%	74.0%	78.0%	78.3%
Recall	76.4%	79.0%	71.4%	77.6%	73.2%
Accuracy	92.5%	94.0%	93.4%	94.6%	94.2%

TABLE II: Table of change mode detection

	GHAC	Our approach
Precision	30.1%	78.0%
Recall	99.0%	77.6%
Accuracy	71.8%	94.6%

B. Experiment

We set a fixed sliding window of size $\delta = 5$ samples, and the sliding step size of 1. Since, it shows a good trade-off between precision and delay. The table I shows the precision of using different δ size. In each step, we calculate the new value for GHAC data by averaging the observations. Then those values are used for computing the activity and comparative angle using (2) and (3) respectively. Consequently, we get the *state vector* S in (4) and identify the changes of transportation mode using (5) from which we filter out the false detections that fall in (6).

The error measure is assessed using the precision (7) and recall (8) metrics that are defined on section II-F. Since the target variable data are skewed class, e.g., only 12% of the data represent change modes. Considering only the accuracy metric (9) is not a meaningful reference, because the data are skewed class, which in the hypothetical case of our technique will evaluate whole the observations as changes, it will provide us an accuracy of 88%. Yet, it does not mean that it is a good detector of changes. For that reason, we consider the precision and recall metrics as references to show the increase of valid detections.

Our approach detects a change of transportation as a specific point in the timeline, depicted in Fig. 3. Thus, we count as a true detection, when the detected change overlaps any of 1s values on the target variable.

The table II shows the result of applying the approach using a fixed-window size of 5 samples; we increase the precision from 30.1% to 78.0%, it means a reduction of precision error from 69.9% to 22.0%. Besides, the accuracy is increased from 71.8% to 94.6%. Although, we notice a decrease in recall from 99% to 77.6%, since our method reduces the over over-segmentation, which is presented on the original GHAC data.

IV. Related works

Most of the researches are focused on the transportation mode classification. To achieve it, researchers use sensors such as GPS, Accelerometer, GSM, Wireless, and Bluetooth. For getting a high accuracy, researchers mainly work with GPS and accelerometer data, although these sensors demand more energy for collecting the tracking data [17].

The tracking data can be categorized either single or multimodal journeys. A single modal journey is a trip where the subject performs a single transportation mode; by contrast, a multimodal journey is a trip with more than one transportation mode [10]. The multimodal journeys are more challenging than single modal one, since multimodal journeys require identifying the different transportation modes along the journey, in other words, identify whether there is a change of mode.

Approaches for transportation mode classification on single mode journey were presented by [18] an approach that uses accelerometer data for inferring the transportation mode, the model has an accuracy of 82.1%; In [12], a transportation mode classification system uses five biaxial accelerometers for gathering the data and asseting the transportation mode, the method achieves 84% of accuracy, although the activities were performed indoors the laboratory, where the individuals may present unusual behavior. GPS and accelererometer data were used in [6]; in [1], an approach uses a mobile phone for collecting the data, and this model achieves an accuracy of 93.6% however, the authors omit the segmentation issue and filter out ambigous states. In addition, approaches for multimode journeys using GPS were presented by [2], a model achieves an accuracy of 90%; in [19], the classifier combines the GPS data with commonsense knowledge of read-world constraints, where a change may occur when there is a walk segment; in [4], an approach aims to classify multimodal journeys by using GPS data, and this model has an accuracy of 88%.

Segmentation is a challenging issue within activity recognition, and it can be achieved by detecting the transition between transportation modes. In [9], the approach splits the trajectories using features from GPS data such as speed and distance. It applies a good commonsense knowledge of the world, describing that the start and end points of walk segment may be changes of transportation mode. In [5], an approach partitions the trajectories into walk segments using speed, distance, angle of point, and acceleration; this segmentation aim to improve the traffic condition. In [2], an approach estimates the changes location using a probabilistic model. In [3] a method identifies changes by detecting walk segments from a trip, despite its accuracy for detecting transportation mode is around 76%, the precision for change detection is bellow 30%.

All those approaches work with features like speed, duration and distance, which are provided by sensors. By contrast, our method works with activity classification data rather than low-level data; therefore, it can work as complement of those approaches.

V. Conclusion

In this paper, we present a novel approach for detecting changes on multimodal journeys. This approach uses the output data of Human Activity classification as input data, which are obtained from the GHAC API. The approach involves a transformation from the original sample space into orthogonal space; then the projected angles are calculated for each axis using a sliding windows, where the axes represent activities such as driving, biking and walking; finally we detect changes on the transportation mode by comparing a state vector in which the projected angles are related each other.

In the preprocessing stage (section II-C), we found two main reasons for incomplete journeys: the first one is due to user input mistakes either selecting the transportation mode or pausing the journey, thus the journey is stopped or deleted; and the second reason rarely present, it is as consequence a system failure, which ends abruptly the application.

The experimental results show increment in the precision, due to reduction the false detections. Thereby the journeys are not over segmented into multiples trips. Although the recall metric is reduced, the accuracy for detecting changes is increased. The effect on recall is explained by the reduction on false detections, this also affects on a small amount of true changes.

Moreover, the presented approach can work as complement of activity classification techniques, since it reduces the over-segmentation by identifying the change modes, and consequently it will increase their accuracy. This approach can be applied to on-line detection for embedded systems, because it involves low computational cost. And the information where people change of transportation, it can be used in other contexts, for instance: to optimize frequencies and trajectories of public transportation such as buses and trams; from a commercial point of view, this information will help to place services on the more likely locations of potential targets.

Further works, in order to improve even more the segmentation for multi modal journeys, we want to incorporate external events like purchasing of electronic tickets, parking lots, bus stops and station boundaries. Those events will help us to make a differentiation between similar transportations such as car, bus, and tram especially in urban places where those vehicles share common routes.

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